INTERNATIONAL CENTRE *for* THEORETICAL SCIENCES

ICTS NEWS

VOLUME X
ISSUE 2
2024

TATA INSTITUTE OF FUNDAMENTAL RESEARCH

THE MACHINE LEARNING CONTRIBUTIONS BEHIND THE 2024 PHYSICS NOBEL PRIZE

HUGO TOUCHETTE

What is Machine Learning?

When we say that we have learned a task or a theory, what we mean truly is that we have learned a description of that task or theory. For a theory, it also means more precisely that we have learned to describe a set of data or observations using a model, so we have developed or *fitted* a model to some part of the world that interests us.

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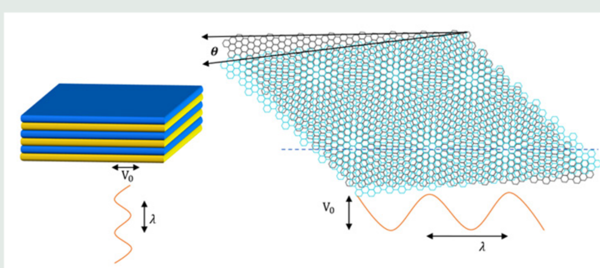
MOIRÉ MATERIALS AS TOPOLOGICAL QUANTUM MATTER SIMULATORS

MANDAR M. DESHMUKH, SUBHAJIT SINHA, PRATAP CHANDRA ADAK

Materials, and technologies emerging from them, have played a central role in human evolution – especially over the last century. Structuring materials have realized new functionalities that do not exist in natural materials. An example is the layered semiconducting heterostructures discovered in the 1970s by growing alternating thin layers of quasi-two-dimensional semiconductors with differing band gaps.



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MAGNETIC RECONNECTION: PLASMA PHYSICS OF SOLAR FLARES AND AURORAE

PALLAVI BHAT

On the nights of May 10-11 this year, the skies lit up with displays of the Aurora Borealis and Aurora Australis, visible in the northern and southern skies, respectively. These light shows are typically visible only from regions within a narrow band of latitudes that occur within a radius of 2500 kilometers of the North Pole, centered around 67° latitude, also known as the Auroral Zone. However, on this particular night, the aurorae were seen at latitudes as low as Leh, Ladakh, at $\sim 34^\circ$ in India. It was a rare event that was witnessed all over the world. Its unusual occurrence was triggered by an energetic geomagnetic storm, with an intensity of the kind that has not been seen since 2003.

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HUGO TOUCHETTE | *continued from Page 1 ...*

THE MACHINE LEARNING CONTRIBUTIONS BEHIND THE 2024 PHYSICS NOBEL PRIZE

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This description of learning is reflected in the modern teaching of ML, which sees learning as fitting functions or models to observations. In the simplest case, we imagine collecting a bunch of observations in the form of inputs $x_1, x_2, \ldots$ leading to outputs $y_1, y_2, \cdots$ via some mapping or function $y = f(x)$. The "true" f is determined by the world – our goal is to find it or model it. For this purpose, we choose a certain approximation $f_\theta(x)$ of this function, involving a set of parameters θ , and attempt to fix all the parameters in θ to get closest to predicting the outputs y_i coming from the inputs x_i. In the process, we say that we *learn* the parameters or that we *learn* f.

This procedure can be extended to learn many other things, including dynamical systems, probability distributions (e.g., the distribution of cat pictures), models that classify data without outputs or labels, and control strategies or policies to guide systems (e.g., cars) automatically. In this context, machine learning is learning done by a machine – a computer.

Like many scientific disciplines, ML covers a vast area combining many different subjects, including neuroscience, mathematics, statistics, physics, engineering, and computer science, to name only these. This year's Nobel Prize in physics is related to a specific domain or application of ML associated with *artificial neural networks* – the main technology driving the rapid expansion of ML seen now in everyday life and science.

Hopfield Networks

Neural networks have a long history in artificial intelligence (AI) and computer science, dating back to the work of McCulloch and Pitts in 1943, who introduced the first mathematical model of neurons called the perceptron [2]. John Hopfield's work [3], which earned him the Nobel Prize, is based on this model and the idea, specifically, that perceptrons could be connected together to build a dynamical system that stores information in the form of learned patterns.

Figure 1: John Hopfield (left) and Geoffrey Hinton (right). John Hopfield received his PhD in Physics from Cornell University in 1958 and worked for most of his career at Princeton University. Geoffrey Hinton received his PhD in AI from the University of Edinburgh in 1978 and went on to work in the US before moving to the University of Toronto, Canada. (Image: Nobel Prize press release. © The Royal Swedish Academy of Sciences)

These networks of connected perceptrons are now called Hopfield networks. They consist, as shown in Fig. 2, of N nodes or neurons x_i that can take the value -1 or 1, which are all connected together by links carrying a weight W_{ij} between node i and j. The weights determine the connection strength between the neurons and their dynamics according to

$$x_i(t+1) = \mathrm{sgn}\left(\sum_j W_{ij} x_j - b_i\right)$$

which is a dynamical version of the perceptron model involving the sign function as well as bias parameters b_i acting on each neuron.

The interesting property of this model is that it can reach a set of pre-determined states or patterns, such as the pattern corresponding to the letter J in Fig.3, in the long-time limit starting from a range of noisy initial patterns (e.g., the noisy J in Fig.3). In this sense, a Hopfield network can decode, associate or store patterns in the attractors of its collective

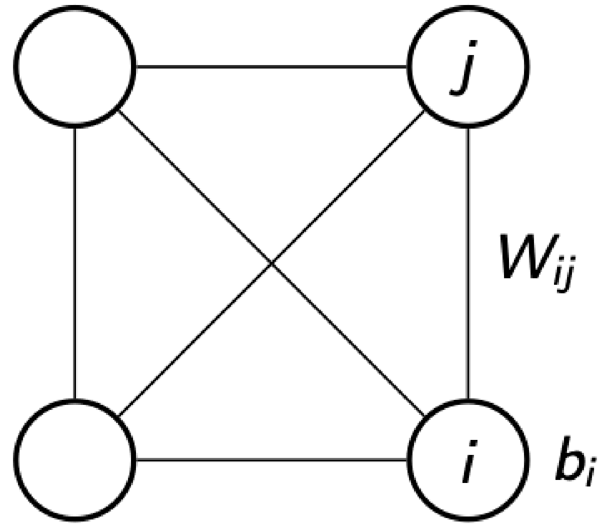

Figure 2: Hopfield network.

dynamics. From a learning point of view, it also represents with the correct weights the map that takes noisy patterns to decoded patterns.

Hopfield described this dynamics in detail in his now famous articles from 1982 and 1984 [3] (see also [4-6] for a more modern presentation). There he shows that multiple patterns can be stored with appropriate weights and, significantly, that the dynamics of the network as a whole can be seen as minimizing an energy function having the form

$$H(x) = -\frac{1}{2}\sum_{ij} W_{ij} x_i x_j$$

which looks like the Hamiltonian of a spin glass.

This interpretation of the neural dynamics is illustrated in Fig.4 and is arguably the most

INPUT PATTERN SAVED PATTERN

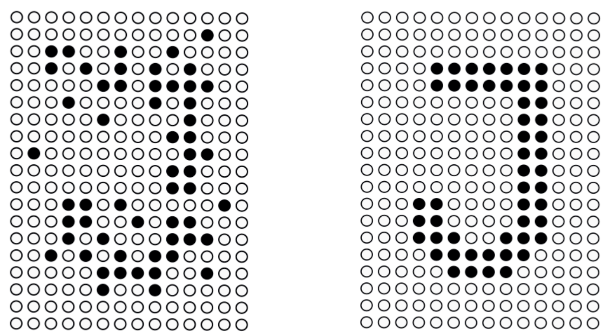

Figure 3: Decoding of a noisy input pattern to a saved pattern. The pixels are the nodes of a Hopfield network. (Image extracted from Fig.4)

important contribution of Hopfield, recognized by the Nobel Prize. By framing learning as an optimization process and by making a connection between neural networks and spin glasses, Hopfield opened a massive door in ML and AI through which many physicists came to learn and do research on these networks. In a short time, this led to the creation of a new field of research exploring the dynamics of neural networks, their capacity to store information, and their ability to learn functions, using concepts from statistical physics and complex systems. This field is very active today and involves a large and interdisciplinary mix of physicists, computer scientists, and other researchers working in AI, who see learning as a physical process.

Learning Distributions

Hopfield put forward the idea that learning

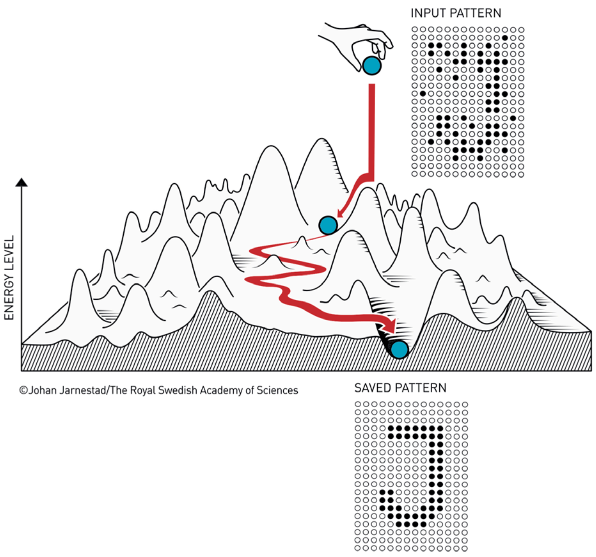

Figure 4: Learning as an optimising dynamics. The decoding dynamics of a Hopfield network minimizes with time an energy function to reach one of its attractor storing a given pattern. (Image: Nobel Prize press release. ©The Royal Swedish Academy of Sciences.)

is a dynamics on an energy landscape, with the minima or attractors of that landscape representing the patterns or data that we want to store or learn. To understand Hinton's contribution and its connection to physics, we need to change that perspective and see instead the data as being encoded in a distribution. The goal then changes from learning a dynamics to learning a distribution.

To understand how this is done, consider the Boltzmann distribution

$$P_\beta(x) = \frac{e^{-\beta H(x)}}{Z(\beta)}$$

and let us imagine that we write a Monte Carlo code to generate a bunch of samples from that distribution using as $H(x)$ the Hamiltonian of a Hopfield network. For a given temperature, we will obtain many different kinds of patterns. However, if we repeat the simulations for smaller and smaller temperatures (that is, larger and larger β), we will see that the patterns sampled become increasingly similar to those coded in the attractors of $H(x)$ This arises because the patterns with the highest probability are those with the least energy.

Editor's Note

The 2024 Nobel Prize in Physics was jointly awarded to the condensed matter, statistical and bio physicist John Hopfield, and the computer scientist and cognitive psychologist Geoffory Hinton, *"for foundational discoveries and inventions that enable machine learning with artificial neural networks"*. Hopfield and Hinton built on earlier work by the neuroscientist Warren McCulloch and the logician Walter Pitts, neuropsychologist Donald Hebb and psychologist and cognitive scientist Frank Rosenblatt. This incredible interdisciplinary breakthrough was enabled by decades of curiosity driven research, in different scientific disciplines, that have now come together in ways that are making an increasing impact on science, engineering and everyday life.

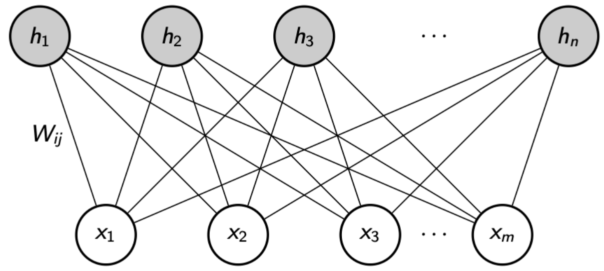

Figure 5: Example of restricted Boltzmann machine

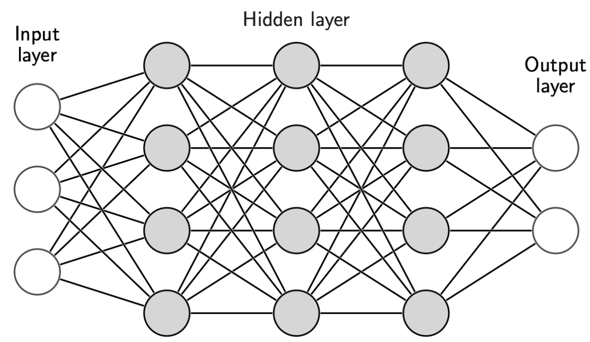

Figure 6: Feedforward neural network. (Image: Izaak Neutelings, tikz.net)

This simulation is interesting because it can replace the Hopfield dynamics: we can start with a noisy pattern and run a Markov chain Monte Carlo simulation from it to reach the correct decoded pattern by lowering the temperature as we run the simulation. This is the idea of simulated annealing. Instead of minimizing a function using a dynamics, we minimize it using sampling.

In this way, we can also learn a distribution. Imagine now that we have a bunch of data, say a sample of proteins in different folded states or a collection of cat pictures, coming from some (unknown) distribution $P(x)$. In the same way that we choose $f_\theta(x)$ to approximate f, we can try to fit $P(x)$ with a certain approximate distribution $P_\theta(x)$ involving some parameters θ, and adjust those parameters to get as close as possible to $P(x)$ based on the data we have. In particular, we can choose P_θ to be a Boltzmann distribution P_β involving some Hamiltonian. In this case, learning $P(x)$ amounts to finding a "good" Hamiltonian that makes P_β close to the "true" $P(x)$.

How do we find this Hamiltonian? Are there simple classes of Hamiltonians that can be used to approximate complex distributions? One such class, developed by Hinton and others from 1985 [7], goes by the name of Boltzmann machines.

Boltzmann Machines

"Hopfield nets used an energy function, and the Boltzmann machine used ideas from statistical physics. So that stage in the development of neural networks did depend - a lot - on ideas from physics." Geoffrey Hinton [8]

The Boltzmann machine modifies the Hopfield network by removing the links between the neurons x_i and by adding a new layer of *hidden* neurons h_α, as shown in Fig.5, connected to the x_i, so the corresponding Hamiltonian is

$$\mathrm{H}(x,h) = -\sum_{i\alpha} x_i W_{i\alpha} h_\alpha - \sum_i a_i x_i - \sum_\alpha b_\alpha h_\alpha$$

where $W_{i\alpha}$ are the weights linking the *visible layer* of neurons x_i to the *hidden layer* of neurons h_α, and a_i and b_α are extra biases or fields acting on each neuron. This is a variant actually of the Boltzmann machine, called the *restricted* Boltzmann machine (RBM).

The motivation for considering this model is twofold: 1 - it is expressive enough to fit or learn many distributions and 2 - it is efficient, in that the weights and biases needed to fit a given distribution can be found directly from the data using a combination of Monte Carlo sampling and gradient descent. These points are discussed in more detail in the talk; see also [6,9] for more information about Boltzmann machines.

What is the purpose of introducing hidden units? When learning the distribution of a bunch of data, we are trying to learn the structure of that data, contained in correlations between the various units . In the Hopfield Hamiltonian, this correlation is accounted for by putting weights between all the units. This leads to an expressive model, but unfortunately it also makes it hard to train.

The idea of the RBM is to introduce correlation between the x_i's not via a direct link between them but via a set of *latent* variables – the hidden units – connected only to the x_i's. The Hamiltonian in this case is still expressive, but can be trained now more easily because all the gradients needed to change the parameters have a simple expression (see the talk or Sec. 16 of [9] for more details).

Concluding Remarks

Neural networks have evolved greatly over the years from the Hopfield and RBM models, but capture the essential ingredients of these models for building efficient learning models. This is exemplified by the networks currently driving ML applications – the feedforward neural networks (Fig.6) – which have hidden or latent layers capturing the structure present in data, and a fully directed architecture that makes the learning of the weight and bias parameters efficient using gradient descent and backpropagation [9].

The 2024 Nobel Prize recognizes the contributions of Hopfield and Hinton to this development, who, for their part, built on a long line of research on AI involving many different disciplines (neuroscience, cognitive science, computer science, etc.) not related *per se* to physics. From a broader perspective, this year's prize is also acknowledging the technological achievements behind the current ML revolution and the deep impact that this revolution is having on society and science, now and for years to come.

Physics is benefiting from this revolution. ML tools and techniques are widely used now for analyzing the tons of data coming from CERN, identifying celestial objects in large astronomical surveys, and designing new materials, among many other applications [10]. At the theoretical level, physicists are also proposing new theories and concepts for explaining why neural networks are good at learning [11]. Finally, in chemistry, ML also made its way with the work of DeepMind to predict the functions of proteins from their compositional sequence – a breakthrough recognized by this year's Chemistry Nobel Prize.

In the end, the ML revolution is not just about applications – it is also about how we think about computing. The way computers work mainly is rooted in logic, Boolean calculus, and procedural programming languages that specify the rules or recipe for calculating functions. Neural networks go counter to this idea. They show that neurons can be stacked as computational units in particular ways to learn functions and compute things efficiently without having (or knowing) any explicit rules.

This shift in computing paradigms is exemplified by ChatGPT as well as engines such AlphaGo or AlphaZero (another invention of DeepMind and the source of AlphaFold) which are able to learn games, like Go or chess, gradually without any explicit rules or knowledge to begin with, beating in the end the best human players. It is only a small step to imagine doing the same in science – that is, to build engines that learn physics or mathematics, say, without "knowing" anything about these subjects.

Further reading

1. Extensive and pedagogical introduction to ML for physicists: [9].
2. Review of ML applications in physics: [10].
3. Recommended textbooks on neural networks, including Hopfield networks and RBMs: [4-6].
4. Definitive source on deep learning, available free on the web: [12].
5. Collection of interviews with many of the people involved in the development of AI and neural networks: [13]. Interesting reading to see that AI is not without controversies as to who really invented Hopfield networks.

Acknowledgements

The section on the Boltzmann machine was greatly inspired by a talk given by Pankaj Mehta on 16 October 2024 as part of the $k \log W$ virtual seminar series organised by the APS.

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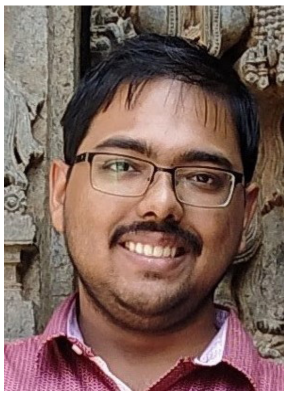
Hugo Touchette is a professor of applied mathematics at Stellenbosch University, South Africa. While visiting ICTS-TIFR in October, he gave a talk explaining the scientific contributions behind this year's Nobel Prize in Physics. This article is a summary of his talk, which can be found on the ICTS YouTUbe channel.

MANDAR M. DESHMUKH, SUBHAJIT SINHA, PRATAP CHANDRA ADAK | *continued from Page 1 ...*

MOIRÉ MATERIALS AS TOPOLOGICAL QUANTUM MATTER SIMULATORS

MANDAR M. DESHMUKH, SUBHAJIT SINHA, PRATAP CHANDRA ADAK



This superstructure made of different layers is called a heterostructure, also called a superlattice, realized a Kronig-Penney model for the electrons moving perpendicular to the plane of stacked semiconductors[1]. Such tailoring of quantum mechanical, electronic states, or bands by introducing another length of the system is a recurring theme for new physics or technology emerging from condensed matter research in the last several decades.

2D Materials – An Expansive Library

A significant advance in condensed matter physics occurred in 2005 when Andre Geim and Kostya Novoselov isolated one atom thick graphite, graphene, and measured its electronic properties by making transistors[2,3]. These discoveries led to the Nobel Prize in 2010 for Geim and Novoselov. Graphene is a two-dimensional (2D) material only one atom thick. Geim and Novoselov isolated a one-atom-thick layer using sticky tape to peel off graphene layers from graphite. The quasiparticles, the low energy charge excitations, in graphene, are described by massless Dirac equation in 2 dimensions $H(k) \propto \sigma_x k_x + \sigma_y k_y$. Subsequently, there has been a revolution because of the community's creativity, and one-atom or few-atom layers of semiconductors, superconductors, and magnetic materials have been realized. Researchers have mined the existing materials database to predict materials with exciting properties that have been experimentally verified. 2D materials have become a promising platform for engineering symmetry properties to realize a variety of

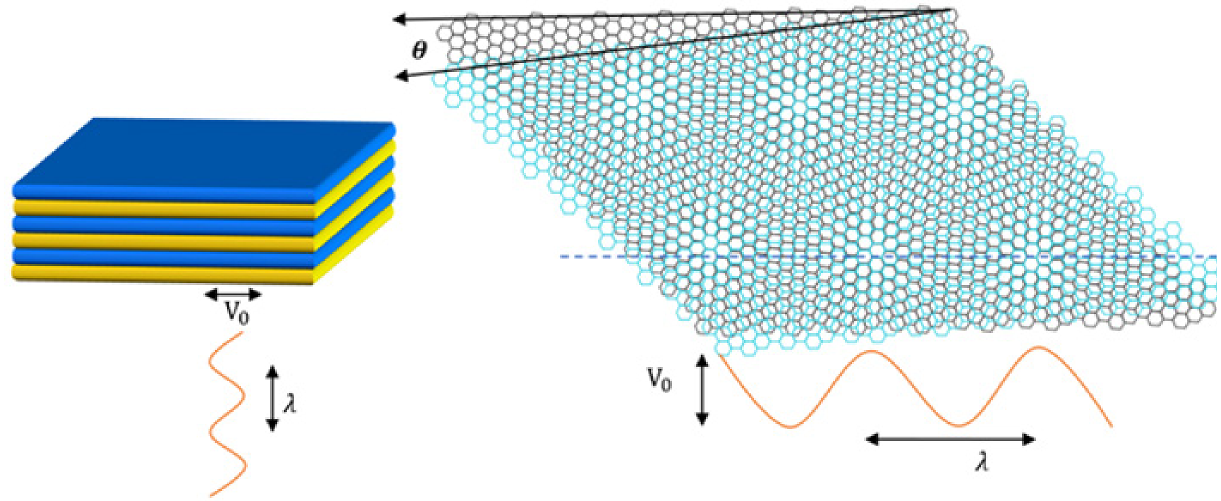


Figure 1: (left) A superlattice created by assembling multilayers of semiconductors. (right) A superlattice is made by twisting two layers of graphene. Twisting two sheets of 2D materials at a small angle θ creates a moiré superlattice with periodicity λ.

Hamiltonians. For example, the effective low energy Hamiltonian for electrons in an inversion symmetric honeycomb lattice is that of massless Dirac fermions. However, when inversion symmetry is broken, the effective Hamiltonian is that of massive Dirac Fermions $H(k) \propto \sigma_x k_x + \sigma_y k_y + \sigma_z \delta$, in 2 dimensions.

Moiré – Rise of Twisted Crystals

In 2018, the exciting experiments by the Pablo Jarillo-Herrero group at MIT [4] opened up a new way to engineer new structures out of one-atom-thick 2D materials. Experiments found that when two layers of a 2D crystal are twisted at arbitrary angles, they form a beating pattern analogous to the beating pattern between

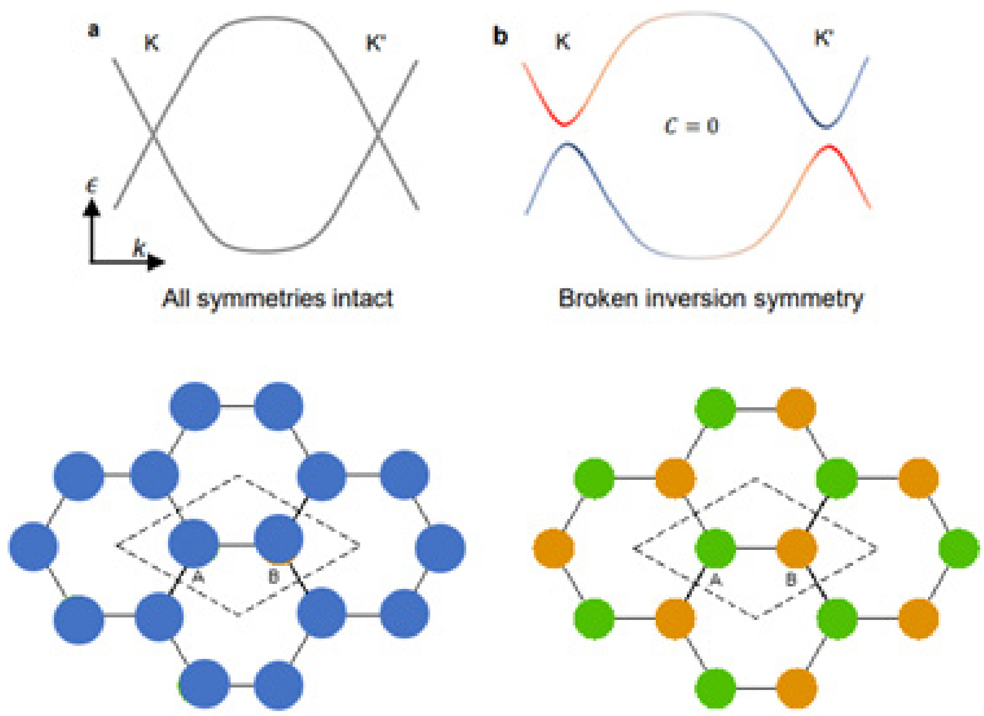


Figure 2: a) Electronic bands and honeycomb lattice with inversion symmetry. b) Gapped bands in a lattice with inversion symmetry broken. The colours indicate the Berry curvature of the bands.

two sound notes. The moiré crystals are thermodynamically unstable but crucially allow tuning of electronic properties by introducing a new length scale and associated energy scale, called the moiré length scale. This new superlattice formed is conceptually similar to the 3D structures formed by stacking quasi-2D layers (Figure 1(left)) but offers a new knob of complex interlayer hopping when twisted by any angle of interest θ (Fig. 1(right)). Tuning the angle gives rise to different band structures[5]– an entirely new way to modify electronic bands now by tuning angle rather than material properties. In addition, the emergent bands can remarkably have profound topological properties - an aspect we will discuss in detail later.

Berry Curvature Physics of Electronic Bands

For several decades, well before the advent of moiré materials, disparate fields of magnetism and quantum Hall effect were trying to develop a deeper understanding of underlying physics. They understood that the topological properties are critical to understanding them both[6]. In some solids, the self-rotation of the electron wave packets leads to sideways deflection of electrons, giving rise to an abnormal velocity. The origin of the self-rotation is the symmetry of the crystal and is reflected in the Berry curvature $\vec{\Omega}$, and when summed over the Brillouin zone, it can give rise to a nontrivial Berry phase. The semiclassical equation of motion of electrons in the electronic bands is written as

$$\dot{r} = \vec{v_g} + \left(\frac{e}{\hbar}\right)\left(\vec{E} \times \vec{\Omega}\right) \text{ and } \hbar\dot{k} = -e\vec{E}$$

Where $\dot{r}$ is the velocity, $\vec{v_g}$ is the group velocity, $\vec{E}$ is the electric field, k is the wave vector, e is the electronic charge, and $\hbar$ is the Planck's constant. $\vec{\Omega}$ is non-zero when either inversion or time-reversal symmetry is broken.

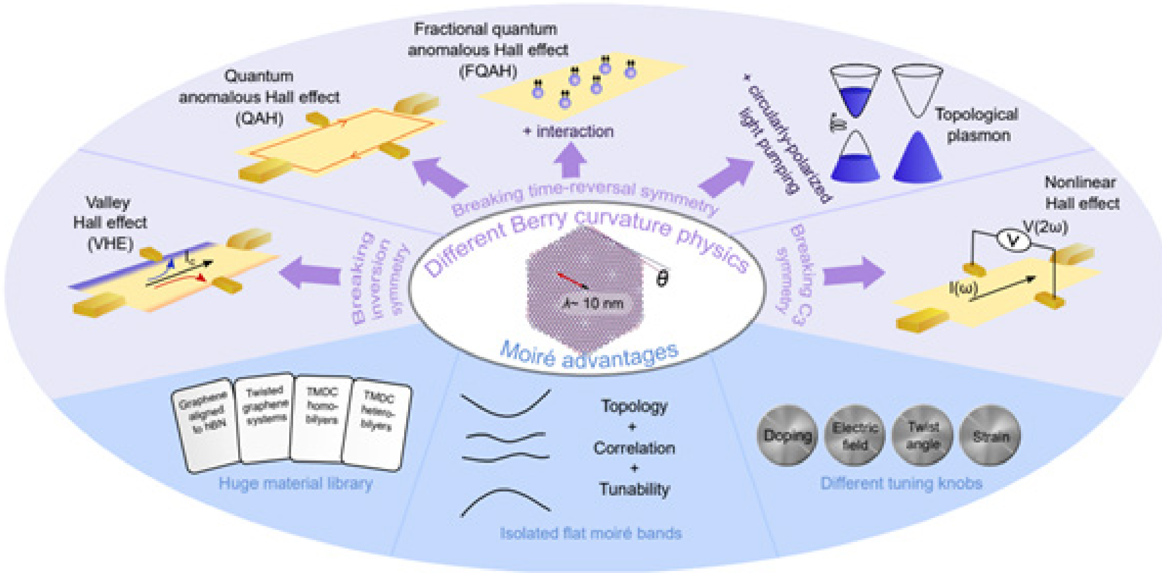


Figure 4: Moiré platform for topology and strong interactions.

Moiré Materials and Topology

The coming together of ideas of topology and moiré has led to a fundamentally new understanding of many aspects of topology and orbital magnetism. The ability to engineer symmetry using materials and tune them using knobs (Fig. 4) like electric fields has also led to new ways to manipulate the valley degree of freedom [7]. For example, breaking inversion symmetry opens up a gap in the spectrum – transforming the Hamiltonian from that of massless Dirac Fermions to that of massive Dirac Fermions. When the spectrum is gapped, a large Berry curvature resides at the edges of the bands, and the two valleys have opposite Berry curvature (Fig. 2). Applying a charge current makes electrons with two different valley flavours move in opposite directions, leading to a valley Hall effect [8].

Strong Hybridization of the Moiré Bands

The twisting of two or more layers of materials leads to the hybridization of electronic states and reconstruction of the bands with dramatic consequences. The twist angle controls the hybridization in a complex, non-monotonic way. When hybridization between the layers is the strongest – when hopping between layers is comparable to hopping between moiré unit cells – the emerging bands are flat (Fig. 3). As many moiré systems break inversion symmetry, they possess Berry curvature in the bands.

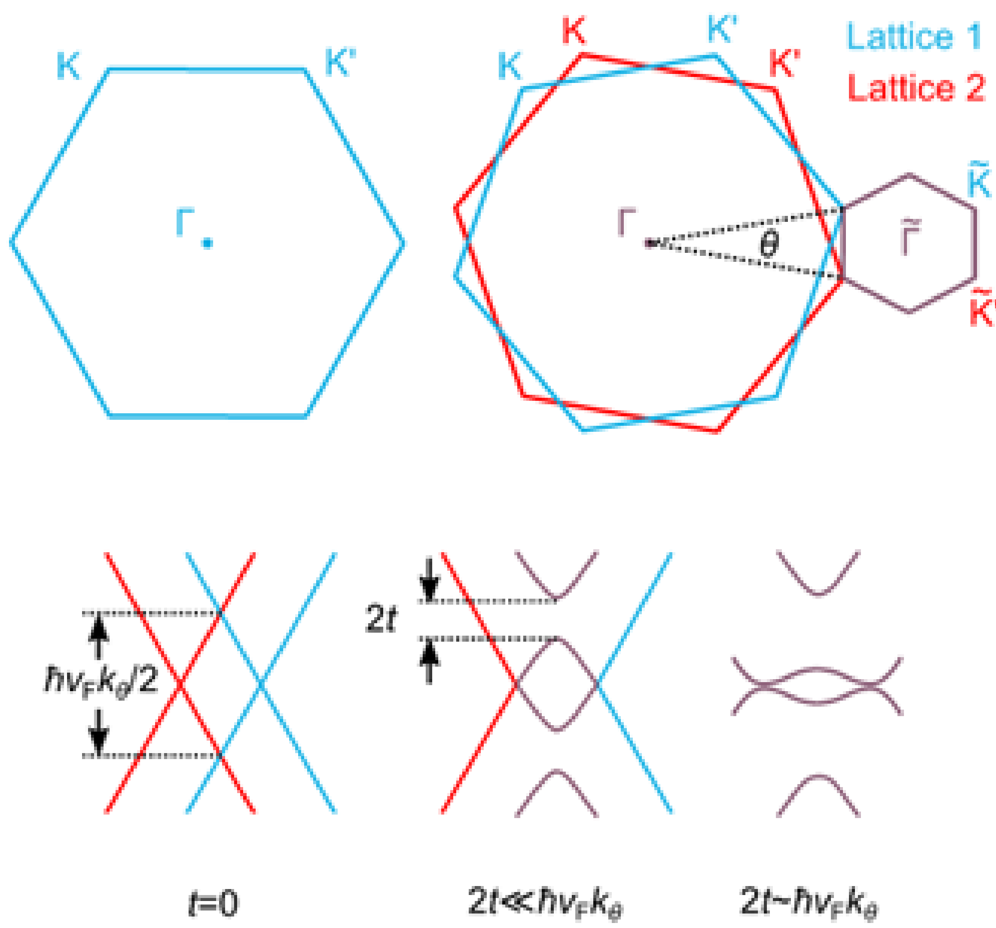


Figure 3: Twisting leads to the hybridization of electronic states from the two layers. Depending on the twisting angle, the hybridization can be tuned. At some precise "magic angles," the hybridization is the strongest, and the emergent bands are flat with narrow bandwidth.

Electronic Interactions – Integer and Fractional Chern Insulators

When the Berry curvature is summed over a single band, the topological invariant is called the Chern number $C = \int_{mBZ} \Omega(k)\boldsymbol{dk}$. The Chern number is non-zero when the time-reversal symmetry is broken. The density of states in the moiré flat bands can be huge; spin and valley exchange energies can spontaneously polarize the bands, leading to broken time-reversal symmetry and a non-zero Chern number. The topological boundary modes are detectable at zero magnetic fields and are called quantum anomalous Hall states. Two flavours of the quantum anomalous Hall effect – the integer and the fractional – have recently been observed in moiré systems. These are the first realizations of the Haldane model in moiré systems and point to exciting studies of the fractional Chern insulating states [9]. There are some fundamentally new open questions about the nature of these fractional quasiparticles. The fact that these quasiparticles can now be realized at zero magnetic fields opens up new possibilities for the future.

Topological Transitions are Sensed Using the First Moment of Berry Curvature

In the presence of time-reversal symmetry and lifting of spatial symmetries, one can see a non-zero first moment of Berry curvature called the Berry curvature dipole. The existence of a Berry curvature dipole leads to a non-linear Hall response. Using the non-linear Hall response, the changes in the Berry curvature and their distributions, when bands touch each other during a topological transition, can be sensed with exquisite detail [10].

The field of moiré materials is rapidly growing and could lead to fundamentally new insights about strong correlation and topology physics. The ability to tune the band structure via knobs, such as density and perpendicular electric field, in the same device offers unprecedented exploration opportunities. However, the reproducibility of these quantum phases across devices has been challenging thus far. Hence, the next frontier in this rapidly evolving field would be to develop local imaging techniques and create detailed spatial maps of the quantum phases of these materials to understand the different factors (such as local symmetries that are governed by substrate alignments, strain, moiré reconstructions) that determine the quantum phases.

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Mandar M. Deshmukh is a professor of physics at TIFR, Mumbai.

Subhajit Sinha is a postdoctoral fellow at ICFO, Barcelona.

Pratap Chandra Adak is a postdoctoral fellow at City College of New York.

BETWEEN THE SCIENCE

RIDDHIPRATIM BASU joined the Editorial Board of the Electronic Journal of Probability (EJP).

MANAS KULKARNI joined the Editorial Board of the Journal of Statistical Mechanics. Prof. Kulkarni was also awarded a CEFIPRA (Indo-French Centre for the Promotion of Advanced Research) grant in collaboration with Gregory Schehr.

ANUPAM KUNDU received the N. S. Satya Murthy Memorial Award of the Indian Physics Association

AJITH PARAMESWARAN was elected as an Associate Fellow of the Indian National Science Academy (INSA).

STHITADHI ROY was selected as an Associate of the Indian Academy of Sciences (IASc).

ASHOKE SEN received the 2024 ICBS Frontiers of Science Award, announced during the International Congress of Basic Sciences (ICSB) in Beijing.

Former graduate student **SUGAN DURAI MURUGAN's** thesis titled *Implications of Inviscid Hydrodynamics and its Variants for Turbulence and Statistical Physics*, received an "Honorable Mention" in the Best Thesis Commendations of TIFR in physics.

PALLAVI BHAT | *continued from Page 1 ...*

MAGNETIC RECONNECTION: PLASMA PHYSICS OF SOLAR FLARES AND AURORAE

PALLAVI BHAT

What is the origin of these fascinating aurorae? These arise primarily due to the interaction between highly energetic charged particles in the magnetosphere — the region around Earth dominated by its magnetic field — and the molecules in the earth's atmosphere leading to colourful radiation. The most common colour is green, resulting from interactions with oxygen molecules at lower altitudes of 100-300 km. A red hue, less frequently seen, arises from oxygen at higher altitudes of 300-400 km. Even rarer are the blue and purple colours, which appear only during intense activity at lower altitudes of around 60 km. The earth's magnetosphere is continuously populated with energetically charged particles by the winds emanating from the Sun. On the occasions when events called solar flares occur, these winds intensify, delivering an unusually large influx of particles that cause geomagnetic storms and heightened auroral activity. Solar flares, therefore, play a crucial role in aurora formation. They are essentially explosive events that occur on or close to the surface of the Sun wherein some of the plasma associated with the Sun is thrown out into space violently, which acutely affects the space weather.

Let us delve into this story in a bit more detail. The Sun, a star at the centre of our solar system, is primarily composed of ionized gas. Most of its energy is carried as radiation up to about 40% of its radius, after which the plasma bubbles up in convective motions. As a dynamic body, the Sun produces magnetic field lines or flux tubes that extend from its surface. Every now and then, these tubes undergo a process known as magnetic reconnection, a highly energetic event that can eject plasma into space. This phenomenon is known as a solar flare. This plasma travels to Earth via the solar wind and interacts with its magnetosphere. Upon interaction, a series of magnetic reconnections take place between the magnetic fields in the solar wind plasma and the Earth's dipolar fields, whereupon the particles get transferred into the magnetosphere. These energetic particles bounce from pole-to-pole gyrating around the field lines, essentially trapped in the magnetosphere. However, a solar flare event in the recent past can cause such particles to slam into the earth's atmosphere, heating it up and causing a glow which we witness as aurorae.

Fig. 1: Shot by Aurorasaurus ambassador Gunjan Sinha, shows the sky on May 11, looking south from near Saskatoon in Saskatchewan, Canada.

We now focus on the plasma physics of solar flares. To do so, we first need to develop some intuition about the way these plasmas behave. Most astrophysical plasmas are highly conducting i.e. the bulk motion of electrons relative to the ions generate currents that have very small resistance. Such resistance is typically due to random Coulomb collisions between ions and electrons. At higher temperatures, the mean free time between collisions increases and as a result, the resistance is lowered. For this reason, astrophysical plasmas which are typically at high temperatures, have high conductance. These plasmas typically also carry random magnetic fields. In the Sun, the magnetic field strength is about 100G (here G ≡ Gauss; for comparison, the earth's magnetic field - which can influence typical handheld compasses - is about 0.5G). These random fields consist of a coherent part that exhibits significant dipolar and quadrupolar components, with the latter being slightly

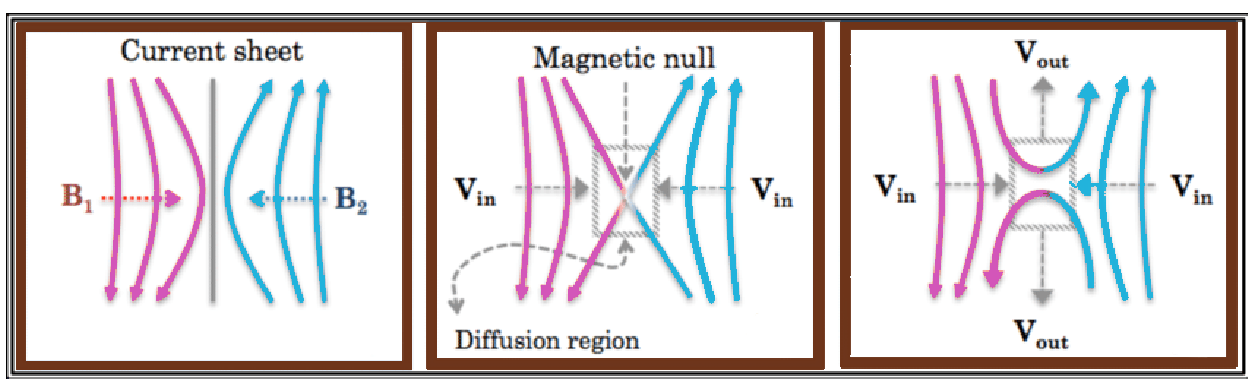

Fig. 2: A schematic depicting magnetic reconnection. Left panel: Oppositely directed flux frozen magnetic field lines brought towards each other by the flow. Middle panel: The field lines interact in the current sheet and are affected by diffusion. Right panel: Reconnected lines leave the reconnection site pushed out due to tension of the elastic fields. Diagram edited from Genestreti et al (2012).

stronger periodically. Such astrophysical plasmas can be treated as fluids when the mean free path between particle collisions is much smaller than the system scale. Equations of magnetohydrodynamics (MHD) can be applied to study their evolution. Apart from the continuity and momentum equation already available in hydrodynamics, a dynamical equation for magnetic field evolution is included in MHD, known as the induction equation. It describes change in magnetic fields due to the flow (or velocity field) of the fluid and also destruction of the fields due to the presence of magnetic diffusivity or resistivity (similar to viscosity in momentum equation).

A special property of highly conducting plasmas is that the magnetic flux is nearly frozen into the fluid. This is exactly true in the ideal limit. Also known as Alfven's theorem, fluid elements connected by magnetic field lines remain magnetically connected at all times as long as magnetic diffusion is negligible (or magnetic Reynolds number is very large). This implies that magnetic topology cannot change in the ideal limit. As these plasmas move and evolve, sharp gradients in the magnetic field can give rise to currents, which can manifest in the form of sheets, thus denoted as current sheets.

If the magnetic diffusivity of the plasma is very small but non-zero, flux freezing can break down at small scales where current density is large. A plasma process known as magnetic reconnection occurs at such sites of large current density. This process involves topological re-arrangement of magnetic fields accompanied by a large release of energy into heat, fluid kinetic motions and particle acceleration.

In Fig. 2, it can be seen that antiparallel magnetic fields are brought towards each other by the flow. At their interface, a current sheet facilitates the breakdown of fluxfreezing, leading to breaking and reconnecting of the fields. The reconnected fields exit the site of reconnection due to tension in the elastic field lines. Reconnection events can be highly energetic and explosive, thus used as a model to understand phenomena such solar flares.

The first established model for reconnection was proposed by Peter Sweet and Eugene Parker in 1956. It is a two-dimensional steady state model which results in a reconnection rate R, proportional to the inverse square root of Lundquist number, S (which is similar to magnetic Reynolds number where the characteristic velocity is given by the Alfven velocity, proportional to the strength of the reconnecting fields; $S = v_A L/\eta$ where η is the magnetic diffusivity) i.e. $R = S^{-1/2}\tau_A^{-1}$, where $\tau_A = L/v_A$ is the Alfven timescale.

This is problematic as solar plasma is highly conducting with values of $S \sim 10^8$ and thus timescales predicted for solar flares are much larger than that observed by a factor of 100-1000. Thus, the Sweet-Parker model turns out to be too slow.

Magnetic reconnection is also very important in the context of fusion physics and magnetic confinement. An avatar of magnetic reconnection known as tearing mode instability was discovered by fusion plasma physicists in the late 1960s [1]. However, tearing mode instability leads to growth rates that are again dependent on an inverse fractional power of the Lundquist number and thus again are slow models. More recently, with the advent of supercomputers, an asymptotic regime for tearing modes was discovered. At very large values of S, above a critical value of $\sim 10^4$, a secondary instability arises which breaks up the current sheet into multiple smaller ones, leading to multiple X-points for reconnection. This is known as the plasmoid instability, named due to the emergence of small islands or plasmoids in the thin current sheets [2]. At steady state, this leads to a reconnection rate independent of the Lundquist number, with $R = 0.01$ [3].

Plasmoid instability has solved the problem of slow timescales and can explain the timescales associated with solar flares. In general, plasmoid instability has led to a flurry of interesting new results. The more prominent one has been its ability to provide an alternative explanation for the origin of cosmic rays in high energy systems (with relativistic plasmas). The high reconnection rate is particularly amenable for efficient particle acceleration [4, 5]. At ICTS, a very recent paper has shown its applicability to explain cosmic rays in galaxy clusters that show presence of diffuse radio emission on scales of the entire system (going out to mega parsecs, where 1 parsec = 3 light years) [6]!

Coming back to the context of the Sun, many questions related to solar flares remain to be answered within the magnetic reconnection model. These include: (i) the trigger/onset problem: reconnection can often occur impulsively with a rapid onset after a slow build-up of energy. What determines the trigger? (ii) energy conversion budget: what is the fraction of energy released into heat, kinetic motions and particle acceleration?

What determines these fractions? These questions will be important to assign some predictability to the occurrence of solar flares and how they affect the space weather. Another important piece of this story is the solar wind. As a solar flare occurs, a blob of solar plasma thrown out into space is carried away by the solar wind. An outflowing wind is a natural steady solution for stars under the spherical symmetry approximation and was first derived by Eugene Parker. A student of Subrahmanyan Chandrasekhar, who contributed immensely to the field of astrophysical fluid dynamics. The Parker wind solution is basically the opposite of Bondi accretion (that occurs typically around compact objects). What powers the solar wind is yet another unknown and is on the list of scientific goals for the Parker solar probe, the only space instrument named after a living scientist. India's Aditya-L1 mission, launched on September 2, 2023, also aims to study the solar wind plasma, in addition to origin, development, and propagation of ejected solar flare plasma.

By unraveling the mysteries of solar flares, magnetic reconnection, and the solar wind, we edge closer to a comprehensive understanding of the Sun's dynamic influence on our solar system. Missions like Aditya-L1 and the Parker Solar Probe will be pivotal in uncovering answers, bridging the gaps in our knowledge, and advancing space weather forecasting for the benefit of life on Earth.

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Pallavi Bhat is a professor of physics at ICTS-TIFR.

PROGRAMS

Quantum Many-Body Physics in the Age of Quantum Information
25-29 November 2024 ✦ *Organizers* — Subhro Bhattacharjee, Manas Kulkarni, Sthitadhi Roy (ICTS-TIFR, Bengaluru) and Subroto Mukerjee (IISc, Bengaluru)

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Magnetic Reconnection: The Engine Behind Solar Flares and Aurorae
25 August 2024 ✦ *Speaker* — Pallavi Bhat *(ICTS-TIFR, Bengaluru)* — J. N. Planetarium, Bangalore

Hyperbolicity
28 July 2024 ✦ Speaker — Indira Chatterji *(Université Côte d'Azur à Nice, France)* ✦ *Venue* — J. N.Planetarium, Bangalore

Tadashi Takayanagi (Yukawa Institute for Theoretical Physics, Japan) delivers his ICTS-Infosys Chandrasekhar Lecture titled *Entanglement and Emergence of Gravitational Spacetime*. Photo credit: **A.S. Sumukh**

Rob Meyers (Perimeter Institute for Theoretical Physics, Canada) talks to young students after his Distinguished Lecture titled *Why We Explore?* Photo credit: **A.S. Sumukh**

ICTS NEWS

International Centre *for* Theoretical Sciences

TATA INSTITUTE OF FUNDAMENTAL RESEARCH

VOLUME X
ISSUE 2
2024

Editor - Ananya Dasgupta
Design - Roshni Samuel

ICTS International Centre *for* Theoretical Sciences
TATA INSTITUTE OF FUNDAMENTAL RESEARCH

ICTS Permanent Address
Survey No. 151, Shivakote village, Hesaraghatta Hobli, North Bengaluru, India 560089
Website www.icts.res.in